DOI: 10.1111/fire.12277

ORIGINAL ARTICLE

The Financial Review WILEY

Network centrality and value relevance of insider trading: Evidence from Europe

Mansoor Afzali[1] | **Minna Martikainen**[2]

[1] Hanken School of Economics, Helsinki, Finland

[2] University of Vaasa, Vaasa, Finland

Correspondence
Mansoor Afzali, Department of Accounting, Hanken School of Economics, PO Box 479, FI-00101 Helsinki, Finland.
Email: mansoor.afzali@hanken.fi

Abstract

We examine the value relevance of insider trades in Europe and find that both purchases and sales of well-connected insiders are positively associated with long-term abnormal returns. We argue that the market perceives the purchases of networked insiders as more informative, leading to higher returns. For sales of networked insiders, the market decreases their negative information content, leading to lower negative returns. Our results do not support the view that insiders use their informational advantage to extract economic rents in the form of dollar profits. We posit that they use their networks to provide signals to the market when trading.

KEYWORDS
governance, insider trading, network centrality, trust, value relevance

JEL CLASSIFICATION
G14, G34, G39

1 | INTRODUCTION

With the technological revolution, the dissemination of information and its importance have reached new levels. Any increment in information or channels thereof can play a significant role in giving a business or an individual a competitive edge. The primary source of acquiring such channels of information and resource exchange is social networks (Cohen et al., 2008; Ferris et al., 2017a). Extant literature in sociology and economics links social networks to almost

every economic activity. Recent studies in the fields of accounting and finance extensively examine the influence of networks on an array of corporate and individual outcomes. Relatively fewer studies, however, delve into assessing the net economic impact of networks (Larcker et al., 2013). We add to this literature by examining the economic effects of networks. More specifically, we study the long-term value relevance of insider trades conditioned on the centrality of their networks in 16 European countries.

Recent evidence from the United Kingdom in Goergen et al. (2019) suggests that purchases by well-connected insiders impact only short-term valuation. The authors argue that networked insiders are more likely to have firm-specific information as well as information on peer firms and broader industrial and economic trends. Their findings show that well-connected insiders trade less frequently and for smaller values while earning short-term profits when purchasing. As previous studies document robust long-term valuation consequences of insider trading (e.g., Huddart & Ke, 2007; Ke et al., 2003; Ravina & Sapienza, 2010) and networked insiders have an informational advantage through their extensive channels of communication and resource exchange (Javakhadze & Rajkovic, 2018; Javakhadze et al., 2016a; Larcker et al., 2013), we reexamine the trading patterns of well-connected insiders and assess the long-term valuation consequences of their trades.[1]

We also examine whether networked insiders exploit their informational advantage and trade to earn long-term abnormal dollar profits or whether they trade to convey signals about future firm prospects. On the one hand, the trading patterns documented in Goergen et al. (2019) may reveal that networked insiders trade consistent with the information-content hypothesis by providing the market with useful signals on the firm's future prospects when purchasing (Ke et al., 2003; Piotroski & Roulstone, 2005). On the other hand, extant literature on network centrality shows that networks can facilitate entrenchment (El-Khatib et al., 2015), increase trading costs (Cai et al., 2016), impair audit quality (He et al., 2017), and transmit information that sophisticated traders can exploit (Akbas et al., 2016). Therefore, we reassess the relation between network centrality and long-term abnormal dollar profits.

To estimate an insider's network, we use insider-level data obtained from BoardEx. BoardEx provides data on connections of executive and nonexecutive directors, as well as senior managers of a firm. We use this information to estimate three well-known centrality measures for each insider—degree, closeness, and eigenvector centrality. Degree centrality measures the total number of direct connections an insider possesses and is widely used as a proxy for total network size (e.g., Ferris et al., 2017a, 2017b; Goergen et al., 2019; Javakhadze et al., 2016a). Closeness centrality captures how close the insider is to other managers and directors. Although degree and closeness centrality measure the size of the network, they do not capture the importance of the connections. Eigenvector centrality not only accounts for the centrality of an individual insider, but also measures the centrality of other insiders to which the individual is connected. It attributes greater weight to connections with more-central insiders and is widely used in the social networks literature (e.g., Bajo et al., 2016; El-Khatib et al., 2015; Larcker et al., 2013). Like Horton et al. (2012), El-Khatib et al. (2015), and Goergen et al. (2019), among others, we limit our network to professional connections formed through boardroom interlocks of public firms.[2] However, while we study insider trading patterns in 16 European countries, we do not limit our network measures to these countries.[3] Instead, we capture the entire network of an insider in Europe by including the insiders of all publicly listed firms with available information on BoardEx Europe and BoardEx United Kingdom. We follow Larcker et al. (2013) and create quartile ranks of our centrality measures to reduce the influence of extreme values, to make regression results easy to interpret, and to account for the upward trend in network size over time.

We obtain insider transaction data from 2iQ Research, which provides global insider transaction data for over 50 countries and more than 200,000 insiders from over 60,000 companies.[4] The insider transaction data provided by

[1] Throughout this paper, we use the terms "well-connected," "networked," and "more-central" to describe insiders with superior networks.

[2] In untabulated results, we show that using the total number of direct connections for an insider with other individuals through their company affiliations in public, private, political, educational, and social organizations, does not alter our main inferences.

[3] The 16 European countries include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Switzerland, Sweden, and the United Kingdom.

[4] 2iQ Research, accessed October 1, 2019, < https://www.2iqresearch.com>

2iQ Research contain detailed accounts of each insider trade (which includes a unique insider identifier key), insider name, company name and international securities identification number (ISIN) for the security traded, transaction date, transaction type (e.g., regular market transaction, exercise of options), transaction value in shares and euros, and the exchange on which the transaction takes place. We use this information to retain only regular market transactions and exclude all transactions carried out by indirectly affiliated insiders.[5] Following the specifications in Cohen et al. (2012), we also exclude routine transactions because they have no informational value (see, e.g., Cohen et al., 2012; Goergen et al., 2019). We merge BoardEx data with 2iQ Research using insider names and unique company identifiers (ISINs). Accounting data are obtained from Compustat Global.

We obtain firm-specific daily price data from Compustat Global and apply a similar procedure as Brooks et al. (2016) to calculate daily firm-specific returns from prices and price factors in Compustat Global. We then calculate cumulative abnormal returns (CARs) for each insider transaction using Fama and French (1993) and Carhart (1997) four-factor models.[6] We use the residual values from the four-factor model as abnormal returns and add them over 180 and 240 trading days to estimate CARs. We estimate the four-factor model using (−200,−21) trading days prior to the trade date (Fidrmuc et al., 2006; Ravina & Sapienza, 2010). Alternatively, we also estimate CARs using the expanded market model as specified in Fidrmuc et al. (2006). The market model uses lead, lag, and current values of market return to explain variations in the firm-specific returns.[7]

Using this information and shorter return windows, we first find that the market reacts more positively to purchases and sales executed by better networked insiders. However, this effect is only present in our univariate tests. Once we control for other determinants of market reaction to insider trades in our multivariate analysis, the excess return disappears.[8] This indicates that the market either does not perceive trades of well-connected insiders as more informative or fail to capture the signal for long-term valuation. To test whether the trades of networked insiders have long-term consequences for the stock price, we turn to abnormal returns estimated over 180 and 240 trading days using both the four-factor model and the expanded market model.

Using these longer windows, we provide robust evidence that trades of well-connected insiders have long-term valuation consequences. The coefficients on the three measures of network centrality are positive and statistically and economically significant. For instance, purchases (sales) of insiders in the second quartile of degree centrality, outperform purchases (sales) of insiders in the first quartile by 2.679% (2.698%) excess return over 180 days after the transaction date, using the four-factor model. This effect is robust to the inclusion of several, previously documented, insider and firm-specific determinants of abnormal returns to insider trades as well as industry-, country-, and year-fixed effects. We hypothesize that as networks enable well-connected insiders to gather more accurate and timely information, they are more likely to convey this information to the market by purchasing the firm stock. Likewise, as networks are associated with a greater risk of loss of reputation, networked insiders are unlikely to engage in insider selling for opportunistic reasons. Consequently, the market decreases the negative information content of insider sales executed by well-connected insiders. Thus, the long-term abnormal returns for insider purchases (sales) of networked insiders are more (less) positive (negative).

We next examine whether networked insiders trade less frequently and lower volumes of stocks as documented by Goergen et al. (2019) in the United Kingdom. We also test whether networked insiders are more likely to engage in multiple trades on the same day and finally, whether they earn long-term abnormal dollar profits. Consistent with Goergen et al., we find that insiders with large and more central networks trade less frequently and exchange lower volumes of stocks. We also find that networked insiders are less likely to trade multiple times on the same day and

[5] This includes family members of the insiders. We exclude these transactions because it is impossible to estimate network size of indirect insiders.

[6] We obtain factor returns for Europe from AQR Capital Management's Web site. The data are employed in Frazzini and Pedersen (2014). We thank the authors for making the data available publicly. The data were last accessed on October 1, 2020 and are available at: < https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Daily>

[7] The results based on the expanded market model are available in Table A.2 of the Appendix in the Supporting Information.

[8] This result is not in contrast to Goergen et al. (2019) as we continue to document the excess market reaction to trades of well-connected insiders in the United Kingdom.

that they engage in opportunistic sales prior to bad news events. Finally, we show that while trades of networked insiders are associated with long-term valuation consequences for the stock price, they are unable to earn statistically or economically significant long-term dollar profits. Overall, these results suggest that while well-connected insiders have increased access to channels of information and resource exchange, they are less likely to exploit them to extract economic rents.

To reduce concerns of endogeneity and alleviate alternative explanations, we perform several robustness checks. First, we exclude firms from the United Kingdom and rerun our main specifications. Second, we orthogonalize our network measures to reduce the effect of human capital that may be endogenously causing our results. Third, we estimate an instrumental variable regression, where we use two instruments for insider network—the average network centrality of all other insiders in the same city and the average road distance between the headquarter location of the firm and all other regions within Europe. Fourth, we use propensity score-matching to derive a matched sample of transactions, eliminating bias originating due to insider and firm-characteristics. Finally, we apply firm fixed effects to control for time-invariant firm-level determinants of insider trading. Our main inferences remain unchanged across all these specifications and we continue to document the long-term valuation consequences of insider trading contingent on the network size of the insider.

Finally, in our subsample analyses, we identify several cultural and governance-related determinants of the association between network centrality and insider trading. Using European Values Surveys (EVSs), we measure the degree of civic norms and the level of societal trust. We show that trades of networked insiders in countries with higher levels of civic cooperation and trust are associated with higher long-term abnormal returns. We also show that country-level governance and equity-based compensation packages influence the centrality–return relation.

We contribute to the existing literature on social networks and corporate and executive outcomes by studying the net economic impact of connectedness on insider trading. Our findings closely relate to the recent studies in corporate finance, which have linked managerial social networks to executive compensation (Engelberg et al., 2012; Horton et al., 2012), access to financing (Engelberg et al., 2012; Ferris et al., 2017b; Javakhadze & Rajkovic, 2018), investment efficiency (El-Khatib et al., 2015), financial development (Javakhadze et al., 2016b), cash-flow sensitivity (Javakhadze et al., 2016a), corporate risk taking (Ferris et al., 2017a), debt contracting (Fogel et al., 2018), and credit ratings (Benson et al., 2018). We extend this literature and show how insider networks influence the trading behavior of insiders and whether such trades have long-term valuation consequences.

Perhaps closest to our work are the findings of Goergen et al. (2019), who document that networked directors outperform directors with inferior networks in the short run for a broad data set of insider transactions in the United Kingdom. Our paper complements the findings of Goergen et al. but differs along several dimensions. First, our results rely on insider transactions carried out by all insider in the16 European countries instead of insider transaction by directors in the United Kingdom. Second, we find that both purchases and sales of networked insiders have informational value. More importantly, we show that the informational value is long term instead of short term and that well-connected insiders do not earn long-term abnormal dollar profits. Our findings do not support the notion that insiders with large and more central networks exploit their connectedness to extract economic rents. On the contrary, they use their extensive channels of communication and trade in accordance with the information-content hypothesis.

We build on the heterogeneity of our sample and reveal several country-level determinants of the centrality–return relation. These results are unique because previous studies focusing on managerial social capital have left out the impact of culture on both centrality and corporate outcomes. Previous studies in finance allude to the importance of culture in influencing corporate finance (see, e.g., Ahern et al., 2015; Karolyi, 2016). We add to this literature by showing that insider transactions of networked insiders are more value-relevant in societies with higher levels of trust and civic cooperation. We argue that as societal trust and civic norms limit opportunistic behavior, insiders (particularly those with broader network size) are unlikely to exploit their informational advantage. In return, the market in such societies deem their insider trading as more informative and less exploitative, leading to an overall positive relation between centrality and long-term abnormal returns.

The remainder of the paper is organized as follows. Section 2 reviews the literature and presents hypothesis development. Section 3 defines key variables, describes data and methodology, and gives sample statistics. Section 4 discusses our results and robustness tests. Section 5 provides additional analyses. Section 6 concludes our findings.

2 | RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

2.1 | Value relevance of insider trading

Previous literature extensively documents the abnormal stock market returns associated with insider trades. For instance, Hillier and Marshall (2002) show that directors consistently earn abnormal returns following earnings announcements. Friederich et al. (2002) reveal that insiders engage in short-term market timing. Likewise, Aboody et al. (2005) demonstrate that insider trades in firms with greater exposure to earnings quality pricing factor are more profitable. Ke et al. (2003) argue that insiders possess and trade on information regarding accounting disclosures as long as 2 years prior to the disclosure. Fidrmuc et al. (2006) show that insiders with lower ownership earn higher abnormal returns. Studies also reveal that insiders are contrarian traders, that is, they time their transactions based on recent performance (Jenter, 2005; Lakonishok & Lee, 2001).

Insiders can trade for several reasons. First, as managers and directors possess private information, they can trade to inform the public (Fidrmuc et al., 2006; Lakonishok & Lee, 2001; Seyhun, 1986). In such cases, the market perceives these trades as important signals for future prospects of the firm, leading to stock price efficiency and better assessment of the investment projects (Ausubel, 1990; Fishman & Hagerty, 1992; Leland, 1992). In line with this theoretical framework, Morck et al. (2000), Piotroski and Roulstone (2004), and Aktas et al. (2008) provide empirical evidence suggesting that insider trading leads to market efficiency. Recent evidence is also consistent with this notion as it shows that insider trading can predict abnormal returns around corporate events (Cziraki et al., 2019; Rossi & Sahlström, 2019).

In contrast, the rent-extraction hypothesis posits that insiders exploit their informational advantage to extract economic rents. Empirical evidence suggests that insiders manipulate or delay value-relevant disclosures to maintain their informational advantage (Cheng & Kin, 2006; Narayanan, 2000). This makes a compelling case for entrenchment by insiders with private information. Besides these two competing explanations, insiders can also trade for liquidity and diversification reasons, which are generally noninformative and nonopportunistic in nature (Cohen et al., 2012).

2.2 | Networks and flow of information

Structural theories by Lin (1999a, 2001) enable researchers to focus on the patterns and intensity of various network connections and derive distinct mechanisms through which social networks influence corporate and individual decisions. One such mechanism is the increase in the flow of information. Several studies document the significance of social networks in opening new channels of information and resource exchange (e.g., Rauch & Casella, 2003). Enhanced flow of information can also help in improving economic efficiency and increasing coordination, ultimately reducing information asymmetry (Ferris et al., 2017a). Recent research presents consistent evidence with this notion. For instance, networks are shown to play an important role in enhancing firm performance (Afzali & Kettunen, 2020; Horton et al., 2012; Larcker et al., 2013), lowering tax burden (Brown, 2011; Brown & Drake, 2014), improving credit ratings (Benson et al., 2018), reducing reliance on internally generated funds and increasing access to finance (Javakhadze et al., 2016a).

2.3 | Networks and insider trading

Well-connected insiders have larger and presumably more central social and professional networks. Such networks help them in acquiring not only firm-specific information, but also information and trends on peer companies, industry, and the general economy (Goergen et al., 2019). We argue that as (a) networked insiders have superior channels of information and resource exchange (Fogel et al., 2018; Javakhadze & Rajkovic, 2018), (b) corporate insiders are known to trade in shares of their firms based on their informational advantage (Piotroski & Roulstone, 2005; Seyhun, 1986), and (c) insider trades have long-term valuation consequences for the stock price (Aboody et al., 2005; Ravina & Sapienza, 2010), we expect trades of networked insiders to have higher value-relevant information. We therefore construct our first hypothesis as follows:

H1: Trades of well-connected insiders have long-term valuation consequences for the firm's stock price.

Theoretically, networked insiders are equally likely to trade in accordance with both information-content hypothesis and rent-extraction hypothesis. On the one hand, well-connected insiders have more channels of communication, which assists them in acquiring timely firm-specific and nonfirm-specific private information. Social ties, through the power of reputation loss, can limit dishonest dealings in transactions by encouraging more reputable behavior (Kandori, 1992; McMillan & Woodruff, 2000). Sociologists also argue that dense associational networks facilitate a harsher punishment for deviation from norms, which deters individuals from acting opportunistically (Coleman, 1994; Spagnolo, 1999). Furthermore, dense networks assist in reducing information asymmetries between external monitors, leading to more effective oversight (Wu, 2008). In line with this, Jeng et al. (2003) show that reputable executives are cautious in insider trading. Considering this evidence, we state the first part of our second hypothesis as follows:

H2a: Well-connected insiders trade to convey value-relevant information to the market and do not earn long-term abnormal dollar profits.

On the other hand, networks can facilitate entrenchment. For instance, El-Khatib et al. (2015) show that CEOs with more central networks engage in value-destroying acquisitions more frequently than CEOs with relatively less-central networks. Well-connected CEOs are also more likely to avoid the discipline of the market. Cai et al. (2016) show that managers with superior networks increase trading costs for other investors. Evidence also exists that networks impair audit quality (He et al., 2017) and transmit information that sophisticated traders can exploit (Akbas et al., 2016). Therefore, we posit that networked insiders can use their informational advantage to trade in accordance with the rent-extraction hypothesis and construct the second part of our second hypothesis as follow:

H2b: Well-connected insiders exploit their superior networks and trade to extract economic rents in the form of long-term dollar profits.

3 | DATA, SAMPLE SELECTION, AND METHODOLOGY

3.1 | Measures of network centrality

One can infer from the social network theory that the concept of well-connectedness has several dimensions (Larcker et al., 2013). We try to capture these different dimensions by calculating three distinct measures of network centrality. These are degree, closeness, and eigenvector centralities and are defined as follows.

Degree centrality (*DEGREE*) measures an insider's total number of direct connections. Presumably, an insider is more connected if s/he possesses relatively more channels of information and resource exchange. Degree centrality captures the number of first-degree linkages to other directors through professional and social networks. Mathematically, it can be expressed as Equation (1), where $u(i,k)$ represents a direct link between insider i and insider k.

$$DEGREE_i = \sum_{k \neq i} u(i,k). \tag{1}$$

Closeness centrality (*CLOSENESS*) represents how easily or quickly an insider can reach other insiders through professional and social networks. A higher measure of closeness indicates that the insider can access more accurate information easily and quickly, giving him a competitive edge. Mathematically, it can be defined as in Equation (2), where $u(i,k)$ represents the number of direct and indirect ties between insider i and k. Hence, *CLOSENESS* is the inverse of the mean distance between insider i and any other insider reachable from him/her in a network of N insiders.

$$CLOSENESS_i = \frac{N-1}{\sum_{k \neq i} u(i,k)}. \tag{2}$$

Although degree and closeness centralities measure the strength of the network based on its size and reach, eigenvector centrality (*EIGENVECTOR*) captures the significance of each connection. An insider with connections to more prominent and well-connected insiders can give him/her access to more valuable information. Mathematically, eigenvector centrality can be expressed as in Equation (3), where $C_E(i)$ measures the sum of all adjacent vertices' eigenvector centrality scores.

$$EIGENVECTOR_i = \frac{1}{\lambda} \sum_{k=1}^{1} A_{ik} C_E(i). \tag{3}$$

3.2 | Data and sample selection

Our sample is derived from various sources. Insider transaction data come from 2iQ Research. The 2iQ Research data set contains detailed insider transaction information for all insider trades in over 50 countries. The data set is updated daily and contains: a unique transaction identification number for each insider trade, transaction date, transaction type (e.g., purchase or sale), insider name, company name, and ISIN for the security traded, insider connection with the company (direct or indirect), insider hierarchical level (e.g., top five managers), asset class (e.g., equity), exchange on which the security was traded, and a variable indicating trade significance.[9] To refine our sample, we place several filters to exclude less-informative transactions. First, we only focus on trades executed directly by top executives, upper level managers, board of directors, and lower level executives. Second, we exclude all other instruments (e.g., options, convertible bonds, etc.) and focus on equity transactions.[10] Third, we exclude transaction executed through Over-The-Counter (OTC) market.[11] Finally, we only focus on open-market insider purchases and sales in 16 European countries over the period 2004–2018.[12] This gives us a sample of 189,181 trades executed by 29,888 insiders.

[9] Trade significance does not correspond to the importance of the trade but denotes, for example, whether the transaction is an open-market transaction (trade significance = 3) or exercise of options (trade significance = 1).

[10] In 2iQ Research data set, equity transactions constitute more than 88% of all transactions for over 50 countries.

[11] These OTC trades constitute approximately 1% of all transactions for over 50 countries. We follow Cohen et al. (2012) and exclude stock options and other instruments because the insider does not have discretion over the timing of these trades.

[12] The 16 European countries include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Switzerland, Sweden, and the United Kingdom. This limitation mainly arises due to data unavailability issues. We need market returns to calculate abnormal returns and because we can only obtain the market returns and other factors for these 16 countries from AQR Capital Management and Wharton Research

We next differentiate between routine and opportunistic trades following Cohen et al. (2012). Specifically, we define routine trades as those that are executed by an insider in the same month for at least 2 consecutive years. We classify all other trades as opportunistic. As routine trades are unlikely to have any long-term value relevance (Cohen et al., 2012), we only focus on opportunistic transactions.[13]

To calculate the network measures, we obtain data from BoardEx, which is a widely used source for estimating network centralities (e.g., El-Khatib et al., 2015; Fogel et al., 2018; Javakhadze & Rajkovic, 2018). We gather data on all publicly listed firms and their insiders from BoardEx.[14] Using the employment history of each insider, we first construct a data set containing all insider–firm–year combinations, forming a two-way network.[15] We then use Pajek—a software that uses methods in social network analysis—and techniques described in De Nooy et al. (2018) to convert our two-way network into insider-specific (one-way) networks. We assume that a connection is only valid until the two insiders share employment in the same firm. Therefore, our network does not increase monotonically over time. However, as BoardEx's data coverage improves over time by adding more firms, our sample for network analysis also increases over time. For example, in 2004, we have 811,946 edges (connections) between insiders while in 2018, we have more than 2,634,140 edges.[16] Using this information, we calculate annual degree, closeness, and eigenvector centralities for each insider.[17]

To merge the network file with 2iQ Research data set, we require a one-to-one match for company ISIN and a nearly perfect match for insider full name in both databases every year.[18] The matching process eliminates a large portion of the original sample. The sample after matching includes 91,591 transactions executed by 18,390 insiders.[19] To reduce the impact of outliers, make regression results easier to interpret, and account for increase in network size over time, we follow Larcker et al. (2013) and Fogel et al. (2018) and create quartiles of network centrality each year using our three measures of network centrality.

To calculate abnormal returns, we obtain firm-specific daily price data from Compustat Global and daily return factors from AQR Capital Management's Web site. The Web site provides factor returns for 16 European countries and as previously used in Frazzini and Pedersen (2014). We use a similar procedure as Brooks et al. (2016) to calculate daily firm-specific returns from prices and price factors in Compustat Global. Specifically, we estimate Equation (4) for each stock in the sample, where *RETURN* is the return for firm *i* on day *t*. *PRC* is the end of the day closing price, *TRFD* is the total daily return factor, and *AJEXDI* is the daily adjustment factor, all obtained from Compustat Global.

$$RETURN_{i,t} = \ln\left(\frac{\left(\frac{PRC_{i,t}\times TRFD_{i,t}}{AJEXDI_{i,t}}\right)}{\left(\frac{PRC_{i,t-1}\times TRFD_{i,t-1}}{AJEXDI_{i,t-1}}\right)}\right). \quad (4)$$

Data Services (WRDS) World Indices, we focus on these countries. We start our sample in 2004 because 2iQ Research's coverage of firms before 2004 is limited.

[13] In our sample, only 5.51% of trades are routine trades. In untabulated results, we find no evidence of networked insiders engaging in routine trades more often than less-networked insiders.

[14] As our study focuses on European firms, we combine data sets from BoardEx Europe and BoardEx U.K. The data are obtained through WRDS at the University of Pennsylvania. The specific BoardEx file we use to construct our network is called Organization–Composition of Officers, Directors, and Senior Managers.

[15] A two-way network has two different sets of nodes. In our case, insiders (node = unique insider identification number) belong to firms (node = ISIN).

[16] Alternatively, we follow the procedure in El-Khatib et al. (2015) and construct a sample that increases monotonically. In this case, we assume that a connection between two insiders remains valid until one of them dies. Doing so results in over 2.63 million edges in 2004 and 26.24 million edges in 2018. Our results, presented in Table A.3 of the Appendix in the Supporting Information, remain qualitatively similar when we use this sample.

[17] To calculate degree and closeness centrality, we use Pajek (Nooy et al., 2018). To calculate eigenvector centrality, we use Gephi (Bastian et al., 2009).

[18] To match the two data sets, we use the Stata command *matchit*, which deploys an algorithm to match two strings of texts based on similar patterns. The command gives us a similarity score, which ranges between one (perfect match) to zero (no match). We manually check the names for similarity scores less than one and drop all observations where names do not match.

[19] The sample includes multiple trades on the same day. We capture the effect of multiple trades by creating a dummy variable. Our results remain qualitatively similar, if we net out the transactions.

To estimate the market reaction, we calculate 3- and 5-day CARs following the transaction date using the Fama and French (1993) and Carhart (1997) four-factor models as shown in Equation (5). To examine the long-term valuation consequences of trades executed by networked insiders, we follow the previous literature (e.g., Ravina & Sapienza, 2010) and calculate 180- and 240-day CARs following the transaction date.[20] We estimate the four-factor model using (−200,−21) trading days before the transaction date (Fidrmuc et al., 2006; Ravina & Sapienza, 2010).

$$RET\_RF_{j,t} = \alpha + \beta_1 MRET\_RF_{c,t} + \beta_2 SMB_{c,t} + \beta_3 HML_{c,t} + \beta_4 UMD_{c,t} + \varepsilon_{j,t}, \quad (5)$$

where *RET_RF* is the daily return for firm *j*, minus the risk-free rate. *MRET_RF* is the daily value-weighted returns of all stocks in a given country *c*, minus the risk-free rate. *SMB*, *HML*, and *UMD* are the daily return factors for size, value, and momentum, respectively. We use the residual values from the model as abnormal returns and add them over 3 and 5 trading days to examine the market reaction and over 180 and 240 trading days to study the long-term impact. Finally, we obtain firm-specific financial data from Compustat Global. We follow the previous studies on insider trading and control for firm size (*SIZE*), leverage (*LEVERAGE*), percentage of fixed assets (*TANG*), interest coverage ratio (*EBITINT*), accounting performance (*ROA*), and an indicator variable that equals 1 if the firm pays dividends, 0 otherwise (*PAYOUT*). For each transaction, we measure all firm characteristics as of the most recent fiscal year end date. After merging the returns and firm-level financial data with the insider trading sample, our final sample comprises 76,575 total transactions out of which 47,118 are purchases and 29,457 are sales.

To examine the market reaction to trades of networked insiders and to test our first hypothesis, we estimate Equation (6) using industry-, year-, and country-fixed effects.

$$CAR_{i,j,c,t} = \alpha + \beta_1 QNETWORK_{i,j,c,t} + \beta_n Trade\ characteristics + \beta_m Insider\ characteristics + \beta_p Firm\ characteristics + Industry,\ Year,\ Country\ Dummies + \varepsilon_{i,j,c,t}, \quad (6)$$

where *CAR* is either 3-, 5-, 180-, or 240-day CARs for a trade executed on date *t*, by insider *i*, belonging to firm *j*, in country *c*. *QNETWORK* is the annual quintile rank of network centrality for insider *i*, based on *DEGREE*, *CLOSENESS*, or *EIGENVECTOR*. As insider characteristics explain a significant portion of abnormal returns (Hillier et al., 2015), we include insider age, gender, and whether or not the insider holds a prominent managerial position like CEO or CFO. We also control for past return (*CAR (−200, −21)*), transaction size as a percentage of total shares outstanding, and an indicator variable for multiple transactions on the same day. We winsorize all continuous variables at the 1st and 99th percentile and present *t*-statistics based on firm cluster robust standard errors.[21]

3.3 | Summary statistics

Table 1 provides summary statistics for insider transactions as well as insider and firm characteristics. In contrast to the United States, European samples are dominated by purchases (see, e.g., Gębka et al., 2017). The mean *CAR (0,3)* for purchases (sales) is 0.953% (−0.192%). The 5-day CAR is slightly higher for purchases and considerably lower for sales, indicating persistence in the market reaction. The long-term CARs are significantly larger and comparable to those reported in studies in the United States. The average *CAR (0,180)* is 6.276% (−8.953%) for insider purchases (sales). This indicates that insider trades in Europe have long-term value consequences in general. The mean (median)

[20] We also calculate 90-day CARs as a robustness check. All our main inferences remain unchanged if we use the 90-day CARs.

[21] Our main results do not change if we apply two-way clustering using firm and date clusters. These results are reported in Table A.3 of the Appendix in the Supporting Information.

TABLE 1 Summary statistics

	Observations	Mean	SD	P25	Median	P75
Summary statistics for purchases						
CAR (0,3)	47,118	0.953	5.611	−1.863	0.487	3.371
CAR (0,5)	47,118	1.209	6.518	−2.198	0.671	4.035
CAR (0,180)	47,118	6.276	30.019	−11.173	4.685	21.844
CAR (0,240)	47,118	5.201	30.524	−12.440	3.519	20.758
DEGREE	47,118	33.056	34.504	12.000	22.000	39.000
CLOSENESS	47,118	0.128	0.059	0.127	0.148	0.164
EIGENVECTOR	47,118	0.036	0.051	0.009	0.019	0.040
AGE (years)	47,118	53.605	8.574	48.000	53.000	59.000
FEMALE	47,118	0.098	0.297	0.000	0.000	0.000
CEO	47,118	0.196	0.397	0.000	0.000	0.000
CFO	47,118	0.061	0.239	0.000	0.000	0.000
MULTITRADES	47,118	0.237	0.426	0.000	0.000	0.000
TRADESIZE	47,118	0.026	0.076	0.001	0.004	0.017
PASTRETURN	47,118	−3.919	26.150	−19.068	−3.811	11.043
SIZE	47,118	3626.702	10,069.663	104.920	442.716	1798.160
LEVERAGE	47,118	0.168	0.145	0.041	0.146	0.252
TANG	47,118	0.217	0.189	0.058	0.165	0.329
EBITINT	47,118	13.111	107.760	0.349	2.604	7.508
ROA	47,118	0.025	0.105	0.010	0.040	0.068
PAYOUT	47,118	0.571	0.495	0.000	1.000	1.000
Summary statistics for sales						
CAR (0,3)	29,457	−0.192	4.153	−2.269	−0.253	1.717
CAR (0,5)	29,457	−0.374	4.881	−2.743	−0.457	2.006
CAR (0,180)	29,457	−8.953	23.320	−21.154	−8.270	4.054
CAR (0,240)	29,457	−9.851	24.441	−22.358	−8.483	3.967
DEGREE	29,457	28.600	27.914	13.000	22.000	33.000
CLOSENESS	29,457	0.126	0.059	0.126	0.146	0.163
EIGENVECTOR	29,457	0.030	0.046	0.010	0.017	0.032
AGE (years)	29,457	52.710	8.328	47.000	52.000	58.000
FEMALE	29,457	0.064	0.244	0.000	0.000	0.000
CEO	29,457	0.200	0.400	0.000	0.000	0.000
CFO	29,457	0.059	0.235	0.000	0.000	0.000
MULTITRADES	29,457	0.356	0.479	0.000	0.000	1.000
TRADESIZE	29,457	0.036	0.102	0.001	0.005	0.020
PASTRETURN	29,457	1.858	22.720	−10.926	1.023	14.639
SIZE	29,457	4401.810	11,012.630	243.964	854.986	2820.880

(Continues)

TABLE 1 (Continued)

	Observations	Mean	SD	P25	Median	P75
LEVERAGE	29,457	0.148	0.129	0.040	0.126	0.224
TANG	29,457	0.187	0.173	0.055	0.136	0.268
EBITINT	29,457	23.066	115.220	1.011	4.650	12.108
ROA	29,457	0.041	0.095	0.022	0.047	0.081
PAYOUT	29,457	0.522	0.500	0.000	1.000	1.000

Note: This table contains the summary statistics for the insider purchases and sales in all countries. *CAR* is the cumulative abnormal return over the specified number of days following the trade date, multiplied by 100. Firm-specific *CAR* is estimated using the Fama and French (1993) and Carhart (1997) four-factor models over (−200,−21) trading days. *DEGREE*, *CLOSENESS*, and *EIGENVECTOR* is the annual insider-specific degree, closeness, and eigenvector centrality as defined in Subsection 3.1. *AGE* is the insider's age in years. *FEMALE* equals 1 if the insider is a female, and 0 otherwise. *CEO* is an indicator variable equal to 1 if the insider is the chief executive officer, and 0 otherwise. *CFO* is an indicator variable equal to 1 if the insider is the chief financial officer, and 0 otherwise. *MULTITRADES* equals 1 if the insider executes more than one transaction of the same type (purchase or sale) on the same day. *TRADESIZE* is the number of shares traded divided by the total number of shares outstanding on the day of the trade multiplied by 100. *PASTRETURN* is the cumulative abnormal return calculated over (−200,−21) trading days before the trading date. *SIZE* is the market value of a firm in billions of dollars, calculated as the total number of shares outstanding multiplied by the price per share for each trading day. *LEVERAGE* is a firm's long-term debt divided by total assets. *TANG* is a firm's net property, plant, and equipment divided by total assets. *EBITINT* is the ratio of earnings before interest and taxes to interest and related expenses. *ROA* is the ratio of income before extraordinary items to total assets. *PAYOUT* equals 1 if the firm pays dividends, and 0 otherwise. All routine trades, based on the definition provided in Cohen et al. (2012), are excluded.

degree centrality is approximately 33 (22) when purchasing and 29 (22) when selling.[22] The median insider age is 53 (52) years when purchasing (selling). Trades executed by female insiders constitutes only 9.8% (6.4%) of our purchase (sale) sample.

Insiders in the sample make purchase transaction more frequently; however, the average trade size seems to be lower for purchases than sales. This is consistent with the findings of Goergen et al. (2019), among others. CEOs seem to trade more frequently than CFOs in our sample. The average past return is negative for purchases and positive for sales, which is a strong indication that insiders are contrarian traders (Jenter, 2005; Lakonishok & Lee, 2001). The median firm size in the sample is around 442 (854) million euros for purchases (sales). The standard deviation indicates that there is significant variation in the firm size. The average firm has 16.8% (14.8%) long-term debt to total assets ratio. The average profitability, as measured by ROA, is around 2.5% (4.1%). More than half of the sample consists of firms paying out dividends.

Table 2 provides sample statistics for insider transactions by country. The sample is dominated by France, followed by the United Kingdom, Sweden, Finland, and Germany. Purchases dominate sales in all countries except Belgium, France, and Switzerland. Although purchases dominate sales in almost all countries, the mean volume of shares traded is usually higher for sales. The average degree centrality of insiders does not vary substantially across countries. The average market reaction to purchases is positive in all countries except Spain and statistically insignificant in Belgium and Italy. The market reaction is highest in the United Kingdom (2.388%). The average market reaction to sales is negative and statistically significant in all countries except Austria, Belgium, Denmark, Finland, Greece, Ireland, Norway, Spain, and Switzerland. The average market reaction to sales is lowest for Germany (−1.084%) followed by Portugal (−0.804%).

[22] This number is significantly higher than those reported by Goergen et al. (2019). They use an insider's professional network and report an average of 12.33 connections. This is primarily due to our methodology in calculating networks. Instead of focusing on connections within the United Kingdom, we count all connections of an insider in Europe. As some insiders are more connected than others, it makes the data positively skewed. On the other hand, the median values are lower.

TABLE 2 Transaction summary by country

Panel A: Insider trading summary statistics by country: Purchases						
Country	Insiders	Trades	Average trade size	Average degree centrality	*CAR (0,3)*	*t*-Statistic
Austria	166	688	0.031	31.340	0.444	2.006**
Belgium	198	599	0.033	32.891	0.226	0.999
Denmark	316	653	0.026	35.689	0.803	3.654***
Finland	676	4486	0.008	40.476	0.619	8.454***
France	1320	6014	0.027	39.468	0.189	3.208***
Germany	1340	5450	0.024	29.394	0.703	9.354***
Greece	130	1140	0.028	25.438	0.336	2.049**
Ireland	183	331	0.026	32.441	1.605	4.780***
Italy	422	2664	0.014	28.049	0.088	1.016
The Netherlands	346	1234	0.020	40.649	0.208	1.864*
Norway	511	945	0.023	34.326	1.205	5.987***
Portugal	55	2142	0.006	15.935	1.586	15.915***
Spain	569	2893	0.012	35.884	−0.137	−1.506
Sweden	2276	6695	0.020	36.894	0.608	10.229***
Switzerland	40	93	0.028	46.204	0.934	2.454***
United Kingdom	4422	11,091	0.048	29.529	2.388	35.563***
Total	12,970	47,118	0.026	33.056	0.953	36.867***
Panel B: Insider trading summary statistics by country: Sales						
Country	Insiders	Trades	Average trade size	Average degree centrality	*CAR (0,3)*	*t*-Statistic
Austria	75	148	0.044	25.635	0.062	0.142
Belgium	227	847	0.035	26.440	0.129	0.991
Denmark	125	329	0.033	41.094	−0.227	−1.097
Finland	331	4185	0.006	28.439	0.227	3.375***
France	1066	9306	0.029	30.558	−0.163	−3.919***
Germany	693	2495	0.054	26.841	−1.084	−10.936***
Greece	135	589	0.043	25.389	0.365	1.974**
Ireland	69	125	0.067	27.248	−0.482	−1.353
Italy	367	2614	0.019	22.297	0.255	3.723***
The Netherlands	263	967	0.028	35.994	−0.221	−2.046***
Norway	171	241	0.041	25.888	−0.323	−0.967
Portugal	32	247	0.011	22.619	−0.804	−4.052***
Spain	248	1378	0.010	28.100	0.085	0.720
Sweden	1073	2637	0.054	29.456	−0.540	−6.215***
Switzerland	32	120	0.007	62.117	0.242	1.250
United Kingdom	1658	3229	0.095	26.404	−0.461	−6.825***
Total	6565	29,457	0.036	28.600	−0.192	−7.938***

(Continues)

TABLE 2 (Continued)

Note: This table contains the transaction summary for each country. *CAR (0,3)* is the cumulative abnormal return over 3 days following the trade date, multiplied by 100. Firm-specific *CAR* is estimated using the Fama and French (1993) and Carhart (1997) four-factor models over (−200,−21) trading days. Average trade size is the average of number of shares traded divided by the total number of shares outstanding on the day of the trade multiplied by 100. Average degree centrality is the insider-specific total professional network. Professional network is defined as the number of direct linkages with other directors through public organizations computed every year using data from BoardEx database. All routine trades, based on the definition provided in Cohen et al. (2012), are excluded.
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4 | RESULTS

4.1 | Univariate tests

To test our hypotheses, we conduct several univariate tests to determine the market reaction to and long-term value relevance of trades of networked insiders. Table 3 provides the results of univariate tests. Panel A of Table 3 provides univariate test results for insider purchases and Panel B of Table 3 provides results for insider sales. The mean market reaction, as measured by *CAR (0,3)* and *CAR (0,5)*, to purchases of networked insiders is positive and statistically significant at the 1% level. However, the market reaction to insider sales of well-connected insiders is not statistically different to the market reaction to insider sales of less-connected insiders. In contrast, *CAR (0,180)* and *CAR (0,240)* indicate that both purchases and sales of well-connected insiders have long-term valuation consequences. The average difference between the two groups is statistically and economically significant.[23]

Furthermore, Table 3 suggests that well-connected insiders trade lower volumes of stocks and are less likely to trade multiple times on the same day, regardless of when they purchase or sell their company stocks. Female insiders are more connected in our sample, which is why trades executed by female insiders are more likely to fall under well-connected insiders. Insider age is also statistically different between the two groups. Networked insiders belong to larger firms, with more leverage, and higher fixed assets. The proxies for profitability indicate that well-connected insiders have lower interest coverage ratios but higher return on assets. This evidence calls for multivariate regression analysis, which controls for these differences.

4.2 | Long-term valuation consequence of insider trades and networks

We test whether insider transactions of networked insiders are informative in the long run.[24] To do this, we use *CAR (0,180)* and *CAR (0,240)* as our main dependent variables and estimate Equation (6) cross-sectionally over the period 2004–2018. The results reported in Panel A of Table 4 show that insider transactions have significant long-term valuation consequences. The coefficient on *QNETWORK* is positive and statistically significant at the 1% significance level in all the columns and across all network centrality measures. The results are also economically significant. For instance,

[23] For univariate analysis related to CARs, we adjust our degree centrality measure for firm size. Firm size and network centrality of insiders is highly correlated; and, as trades of insiders in small firms generate higher abnormal returns due to higher information asymmetry, our results without this adjustment will simply reflect the omitted variable bias. The adjustment for firm size is based on Larcker et al. (2013). This issue is resolved in multivariate analysis, where we control for firm size.

[24] We examine the market reaction to insider trades in Table A.7 of the Appendix in the Supporting Information. The main variable of interest, *QNETWORK*, which is the quartile rank of one of our centrality measures, has a positive coefficient but is statistically insignificant across all columns. This indicates that the market reaction to insider transaction executed by well-connected insiders is not statistically different than those executed by less-connected insiders. Like insider purchases, we find no evidence of a higher market reaction to insider sales executed by well-connected insiders. This suggests that the insider trades of networked insiders are not more informative in the short run. This is in contrast to recent evidence from the United Kingdom in Goergen et al. (2019). However, as Goergen et al. focus only on firms in the United Kingdom, we repeat our analysis for insiders in the United Kingdom. We find consistent evidence with Goergen et al. as the market reaction to purchases of networked insiders in the United Kingdom is higher and statistically significant.

TABLE 3 Univariate tests

Panel A: Insider purchases				
	Well-connected insiders	Less-connected insiders	Difference	*t*-Statistic
CAR (0,3)	1.139	0.718	0.421***	8.09
CAR (0,5)	1.434	0.926	0.508***	8.41
CAR (0,180)	7.263	5.033	2.229***	8.01
CAR (0,240)	6.926	3.028	3.897***	13.79
MULTITRADES	0.207	0.268	−0.061***	−15.64
TRADESIZE	0.015	0.037	−0.023***	−33.24
FEMALE	0.132	0.064	0.068***	25.02
AGE	54.435	52.792	1.643***	20.89
CEO	0.155	0.236	−0.081***	−22.30
CFO	0.053	0.069	−0.016***	−7.39
PASTRETURN	−3.894	−3.943	0.049	0.20
SIZE	7.290	5.089	2.201***	137.60
LEVERAGE	0.187	0.149	0.039***	29.23
TANG	0.231	0.205	0.026***	14.99
EBITINT	11.800	14.394	−2.594***	−2.61
ROA	0.036	0.014	0.021***	22.02
PAYOUT	0.648	0.495	0.152***	33.84
Panel B: Insider sales				
	Well-connected insiders	Less-connected insiders	Difference	*t*-Statistic
CAR (0,3)	−0.166	−0.210	0.044	0.89
CAR (0,5)	−0.384	−0.367	−0.017	−0.29
CAR (0,180)	−6.372	−10.728	4.356***	15.82
CAR (0,240)	−6.365	−12.248	5.883***	20.44
MULTITRADES	0.331	0.376	−0.045***	−7.97
TRADESIZE	0.019	0.051	−0.033***	−27.61
FEMALE	0.078	0.051	0.027***	9.31
AGE	54.125	51.504	2.620***	27.25
CEO	0.181	0.216	−0.036***	−7.64
CFO	0.060	0.058	0.002	0.67
PASTRETURN	1.201	2.417	−1.215***	−4.58
SIZE	7.838	5.801	2.037***	110.38
LEVERAGE	0.179	0.122	0.056***	38.24
TANG	0.202	0.174	0.028***	13.68
EBITINT	20.356	25.374	−5.018***	−3.73
ROA	0.052	0.032	0.020***	17.92
PAYOUT	0.609	0.447	0.162***	28.19

(Continues)

TABLE 3 (Continued)

Note: This table provides the results for univariate tests. Well-connected (less-connected) insiders are insiders in the top two (bottom two) quartile of *DEGREE* in each year. *DEGREE* is the annual insider-specific degree centrality as defined in Subsection 3.1. *CAR* is the cumulative abnormal return over the specified number of days following the trade date, multiplied by 100. Firm-specific *CAR* is estimated using the Fama and French (1993) and Carhart (1997) four-factor models over (−200,−21) trading days. *AGE* is the insider's age in years. *FEMALE* equals 1 if the insider is a female, and 0 otherwise. *MULTITRADES* equals 1 if the insider executes more than one transaction of the same type (purchase or sale) on the same day. *TRADESIZE* is the number of shares traded divided by the total number of shares outstanding on the day of the trade multiplied by 100. Based on the definition provided in Cohen et al. (2012), all routine trades are excluded.
*** indicate statistical significance at the 1% levels, respectively.

purchases of insiders in the second quartile of degree centrality, all other thing being equal, outperform purchases of insiders in the first quartile by 2.679% (2.878%) excess return over 180 (240) days after the transaction date, using the four-factor model. In Panel B of Table 4, we report results for insider sales. We find that insider sales by well-connected insiders produce less negative long-term excess returns. The results are statistically significant at the 1% level in all the columns and across all network centrality measures. Economically, sales of insiders in the second quartile of closeness centrality, all other things being equal, outperform sales of insiders in the first quartile by 2.569% (3.347%) excess return over 180 (240) days after the transaction date, using the four-factor model. Overall, we find strong support for H1, which states that insider trades executed by insiders with more central networks have long-term valuation consequences for a stock. The results are in contrast to the findings of Goergen et al. (2019), who only document a short-term value relevance of insider purchases by networked directors in the United Kingdom.

We argue that the more positive market reaction to networked insiders' purchases results from the market's perception of these trades in the long run. As networks enhance oversight mechanisms through an increase in risks of reputation loss, well-connected insiders are less likely to engage in opportunistic trades. We posit that the market perceives purchases by well-connected insiders as more informative and less exploitative, resulting in more positive long-term abnormal returns. For sales, we conjecture that networked insiders trade only for liquidation and diversification reasons. Thus, the market decreases the negative information content of these trades, resulting in less negative long-term abnormal returns. We test these conjectures through different specifications.

Among other variables, although, insider purchases by older insiders seem to produce lower excess returns over 180 days; we do not find consistent evidence that insider age plays a significant role in explaining long-term excess returns. Insider gender is also insignificant across all columns and panels. In contrast to Wang et al. (2012), we find that purchases and sales of CEOs have long-term value relevance as opposed to insider trades of CFOs. Transaction size seems to only matter in the case of insider sales. However, this effect disappears when we look at 240-day excess returns. The coefficient on *PASTRETURN* is consistently negative and statistically significant at the 1% significance level for insider purchases and sales. This is in line with previous studies, which show that insiders are contrarian traders (Jenter, 2005; Lakonishok & Lee, 2001). Small firms have higher information asymmetry, which is why the long-term valuation consequences of insider trading in such firms is higher (see, e.g., Cohen et al., 2012).

4.3 | Insider trading patterns, long-term profitability, and networks

We run several estimations to test our second hypothesis and examine insider trading patterns contingent on insider networks. First, we look at the transaction size and frequency. If networked insiders trade to extract economic rents, one might expect them to trade more frequently and larger quantities of shares. On the other hand, social networks may act as a form of social barrier, resulting in fewer trades due to risks associated with loss of reputation. In Table 5, columns (1)–(3), we find that well-connected insiders trade less frequently and lower volumes of shares than less-connected insiders. The coefficient on *QDEGREE* is negative and statistically significant in all the four columns. This

TABLE 4 Long-term valuation consequences of insider trades and networks

Panel A: Insider purchases						
Network measure	*DEGREE*		*CLOSENESS*		*EIGENVECTOR*	
Dependent variable:	*CAR (0,180)*	*CAR (0,240)*	*CAR (0,180)*	*CAR (0,240)*	*CAR (0,180)*	*CAR (0,240)*
	(1)	(2)	(3)	(4)	(5)	(6)
QNETWORK	2.679***	2.878***	3.249***	3.710***	3.095***	3.425***
	(6.83)	(6.88)	(7.23)	(7.40)	(7.48)	(7.62)
AGE	−5.314**	−2.773	−4.438**	−1.893	−5.301**	−2.817
	(−2.49)	(−1.25)	(−2.09)	(−0.87)	(−2.49)	(−1.28)
FEMALE	0.879	1.640	0.822	1.554	0.838	1.584
	(0.89)	(1.56)	(0.84)	(1.50)	(0.84)	(1.50)
CEO	1.070	2.197***	0.999	2.137***	1.110	2.251***
	(1.38)	(2.67)	(1.30)	(2.60)	(1.44)	(2.75)
CFO	−0.677	−0.818	−0.965	−1.120	−0.671	−0.798
	(−0.50)	(−0.58)	(−0.73)	(−0.81)	(−0.50)	(−0.57)
MULTITRADES	0.723	−0.781	0.870	−0.611	0.766	−0.732
	(0.75)	(−0.78)	(0.90)	(−0.61)	(0.79)	(−0.73)
TRADESIZE	8.531**	4.606	9.035**	5.161	8.636**	4.712
	(2.08)	(1.11)	(2.22)	(1.26)	(2.11)	(1.14)
PASTRETURN	−0.394***	−0.391***	−0.395***	−0.392***	−0.394***	−0.390***
	(−20.18)	(−23.73)	(−20.35)	(−23.95)	(−20.16)	(−23.70)
SIZE	−3.069***	−3.071***	−3.329***	−3.432***	−3.265***	−3.319***
	(−11.88)	(−10.90)	(−11.95)	(−11.16)	(−12.33)	(−11.41)
LEVERAGE	9.969***	4.734	9.732***	4.421	9.910***	4.648
	(2.84)	(1.23)	(2.80)	(1.14)	(2.83)	(1.21)
TANG	3.944	1.947	3.356	1.340	4.002	2.043
	(1.57)	(0.75)	(1.36)	(0.52)	(1.59)	(0.79)
EBITINT	−0.000	0.000	0.000	0.001	−0.000	0.001
	(−0.04)	(0.09)	(0.06)	(0.20)	(−0.01)	(0.13)
ROA	−4.022	−4.087	−2.944	−2.683	−3.599	−3.535
	(−0.66)	(−0.63)	(−0.49)	(−0.42)	(−0.59)	(−0.55)
PAYOUT	1.504*	1.532*	1.347*	1.364	1.552*	1.591*
	(1.88)	(1.70)	(1.68)	(1.52)	(1.93)	(1.77)
Intercept	42.896***	23.396	41.300***	21.825	43.120***	23.766
	(4.02)	(1.52)	(3.74)	(1.34)	(4.01)	(1.51)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.213	0.186	0.214	0.188	0.214	0.187
Observations	47,118	47,118	47,118	47,118	47,118	47,118

(Continues)

TABLE 4 (Continued)

Panel B: Insider sales						
Network measure	***DEGREE***		***CLOSENESS***		***EIGENVECTOR***	
Dependent variable:	***CAR (0,180)***	***CAR (0,240)***	***CAR (0,180)***	***CAR (0,240)***	***CAR (0,180)***	***CAR (0,240)***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
QNETWORK	2.698***	3.157***	2.569***	3.347***	2.674***	3.221***
	(4.91)	(5.58)	(5.24)	(6.68)	(4.91)	(5.35)
AGE	1.778	1.152	2.136	1.462	1.806	1.144
	(0.82)	(0.44)	(0.99)	(0.61)	(0.83)	(0.44)
FEMALE	0.140	−0.714	0.268	−0.575	0.136	−0.725
	(0.12)	(−0.54)	(0.22)	(−0.43)	(0.11)	(−0.54)
CEO	0.436	2.298**	0.572	2.458**	0.512	2.385**
	(0.51)	(2.28)	(0.67)	(2.49)	(0.60)	(2.37)
CFO	1.470	2.372	1.516	2.444	1.515	2.429
	(1.05)	(1.43)	(1.11)	(1.50)	(1.08)	(1.46)
MULTITRADES	0.440	0.254	0.491	0.355	0.454	0.280
	(0.53)	(0.23)	(0.60)	(0.34)	(0.54)	(0.24)
TRADESIZE	−12.839***	−12.366***	−12.832***	−12.329***	−12.794***	−12.304***
	(−5.10)	(−3.77)	(−5.07)	(−3.69)	(−5.09)	(−3.74)
PASTRETURN	−0.367***	−0.375***	−0.364***	−0.372***	−0.367***	−0.375***
	(−17.70)	(−17.47)	(−17.41)	(−17.19)	(−17.66)	(−17.43)
SIZE	−1.092***	−1.211***	−1.032***	−1.268***	−1.110***	−1.268***
	(−3.16)	(−3.25)	(−2.88)	(−3.38)	(−3.19)	(−3.37)
LEVERAGE	2.732	−2.305	1.240	−4.332	2.642	−2.436
	(0.71)	(−0.46)	(0.32)	(−0.88)	(0.68)	(−0.48)
TANG	5.880**	9.401***	5.975**	9.643***	5.692**	9.206***
	(2.23)	(3.04)	(2.23)	(3.13)	(2.14)	(2.95)
EBITINT	0.008**	0.007*	0.006**	0.005	0.008**	0.007*
	(2.42)	(1.75)	(1.98)	(1.37)	(2.36)	(1.70)
ROA	−5.634	−6.520	−2.735	−2.560	−5.240	−5.997
	(−0.88)	(−0.96)	(−0.40)	(−0.36)	(−0.82)	(−0.88)
PAYOUT	3.085***	3.772***	2.795***	3.419***	3.069***	3.759***
	(3.38)	(3.45)	(3.06)	(3.20)	(3.35)	(3.45)
Intercept	−23.387*	−19.001	−24.278**	−19.420	−23.034*	−18.382
	(−1.88)	(−1.33)	(−2.00)	(−1.46)	(−1.85)	(−1.29)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.206	0.208	0.205	0.210	0.206	0.208
Observations	29,457	29,457	29,457	29,457	29,457	29,457

(Continues)

TABLE 4 (Continued)

Note: This table contains the regression results explaining the long-term valuation consequences of insider trades based on the centrality of insider networks and other variables. *CAR* is the cumulative abnormal return over the specified number of days following the trade date, multiplied by 100. Firm-specific *CAR* is estimated using the Fama and French (1993) and Carhart (1997) four-factor models over (−200,−21) trading days. *QNETWORK* is the quartile rank formed each year based on the centrality measures. *DEGREE*, *CLOSENESS*, and *EIGENVECTOR* is the annual insider-specific degree, closeness, and eigenvector centrality as defined in Subsection 3.1. *AGE* is the natural logarithm of insider's age in years. *FEMALE* equals 1 if the insider is a female, and 0 otherwise. *CEO* is an indicator variable equal to 1 if the insider is the chief executive officer, and 0 otherwise. *CFO* is an indicator variable equal to 1 if the insider is the chief financial officer, and 0 otherwise. *MULTITRADES* equals 1 if the insider executes more than one transaction of the same type (purchase or sale) on the same day. *TRADESIZE* is the number of shares traded divided by the total number of shares outstanding on the day of the trade multiplied by 100. *PASTRETURN* is the cumulative abnormal return calculated over (−200,−21) trading days before the trading date. *SIZE* is the natural logarithm of market value of a firm, calculated as the total number of shares outstanding multiplied by the price per share for each trading day. *LEVERAGE* is a firm's long-term debt divided by total assets. *TANG* is a firm's net property, plant, and equipment divided by total assets. *EBITINT* is the ratio of earnings before interest and taxes to interest and related expenses. *ROA* is the ratio of income before extraordinary items to total assets. *PAYOUT* equals 1 if the firm pays dividends, and 0 otherwise. The *t*-statistics based on firm cluster robust standard errors are shown in parentheses.
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

indicates that networked insiders are either reluctant to trade due to higher risk of loss of reputation or that such insiders do not exploit their informational advantage to extract economic rents.

Following Ravina and Sapienza (2010), we test whether networked insiders engage in information-related selling before "bad news" events. We define bad news events as days in which the market-adjusted return is less than 5%. We create an indicator variable that equals 1 if the transaction date of the insider trade occurs during the 120 days prior to the bad news event date, and 0 otherwise. Using this definition, we classify 37,822 transactions as occurring prior to the bad news event and 38,753 transactions as nonbad news trades. We test whether insiders are more likely to sell their company's shares if there is bad news event coming up. Therefore, we only focus on the 37,822 transactions. We find that the probability of an insider sale before a bad news event decreases significantly as the insider network increases. The results are provided in column (4) of Table 5.[25]

To test whether insiders earn long-term abnormal dollar profits, we estimate Equation (6), and replace *CAR* with *PROFIT*, where *PROFIT* is defined following Huddart and Ke (2007) as profit (in millions of euros) to insider in a firm-year, computed as annual sum of either 180- or 240-day CARs multiplied by the trade size. In the sum, abnormal returns following sales are multiplied by −1 so that losses avoided on sales are added to gains on purchases.[26] The results for this test are provided in Table 5, columns (5) and (6). In column (5) of Table 5, the coefficient on *QDEGREE* is negative and statistically insignificant. In column (6) of Table 5, the coefficient is negative and statistically significant at the 10% level.[27] This indicates that not only are well-connected insiders unable to earn significant long-term abnormal dollar profits relative to less-connected insiders, but networked insiders seem to earn less. This contradicts the rent-extraction hypothesis, which posits that insiders trade to extract economic rents. Therefore, we find limited support for entrenchment as hypothesized in H2b. Taken together, our results suggest that networked insiders engage in insider purchasing to inform the market and do not exploit their informational advantage when selling, as hypothesized in H2a.[28]

[25] We also re-run our main model and interact the network measures with a dummy indicating a sale prior to a bad news event. We find no evidence that networked insiders are more likely to avoid large losses by selling prior to bad news events. This further indicates that networked insiders do not exploit their informational advantage.

[26] For firm-level control variables, we retain the values corresponding to the last trade of an insider each year.

[27] These results are mainly driven by insider sales. This further supports the notion that networked insiders sell their stock for noninformational reasons.

[28] In Table A.1 of the Appendix in the Supporting Information, we provide several robustness checks for our main specifications, including specifications to address endogeneity concerns.

TABLE 5 Insider trading patterns, long-term profitability, and networks

Regression type:	OLS	Logit	Logit	Logit	OLS	OLS
Dependent variable:	*TRADESIZE*	*MULTITRADES*	*NTRADES*	*BAD NEWS SALE*	*PROFIT (0,180)*	*PROFIT (0,240)*
	(1)	(2)	(3)	(4)	(5)	(6)
QDEGREE	−0.002**	−0.329***	−0.066*	−0.409***	−0.017	−0.011*
	(−2.28)	(−4.10)	(−1.75)	(−7.20)	(−1.38)	(−1.77)
AGE	0.016***	0.389	0.350*	−1.282***	−0.335	−0.128*
	(3.52)	(1.00)	(1.66)	(−4.44)	(−1.60)	(−1.83)
FEMALE	−0.006***	−0.390***	−0.304***	−0.351***	−0.027	−0.008
	(−3.67)	(−2.91)	(−3.31)	(−2.91)	(−1.39)	(−0.92)
CEO	0.014***	0.277**	−0.049	−0.368***	−0.041	0.020
	(7.47)	(2.26)	(−0.60)	(−3.51)	(−0.59)	(0.94)
CFO	−0.008***	−0.150	−0.039	−0.451***	−0.050	−0.015
	(−4.21)	(−1.03)	(−0.41)	(−3.17)	(−1.27)	(−1.59)
MULTITRADES	−0.018***			0.472***		
	(−13.11)			(5.32)		
TRADESIZE		−3.053***	−4.413***	3.729***	0.715	1.138***
		(−9.93)	(−6.55)	(14.72)	(0.87)	(3.60)
PASTRETURN	0.000*	0.000	−0.002**	0.007***	−0.000	0.000
	(1.84)	(0.22)	(−2.05)	(6.25)	(−0.04)	(0.24)
SIZE	−0.011***	−0.121***	−0.049*	0.373***	0.021	0.028***
	(−17.46)	(−3.62)	(−1.92)	(9.29)	(1.44)	(4.36)
LEVERAGE	−0.005	0.256	−0.404	−0.280	−0.003	0.065
	(−0.65)	(0.44)	(−1.30)	(−0.78)	(−0.05)	(0.90)
TANG	−0.007	−0.631*	−0.070	−0.771**	−0.049	0.015
	(−1.25)	(−1.78)	(−0.29)	(−2.29)	(−0.38)	(0.22)
EBITINT	0.000	−0.001*	−0.000	−0.000	0.000	0.000
	(0.99)	(−1.93)	(−0.92)	(−0.51)	(0.48)	(0.03)
ROA	−0.001	0.452	−0.405	0.904**	0.070	0.087
	(−0.06)	(1.11)	(−1.15)	(2.07)	(0.47)	(1.14)
PAYOUT	−0.005***	0.105	−0.013	0.281**	−0.036	−0.024
	(−2.93)	(0.76)	(−0.18)	(2.50)	(−1.28)	(−1.61)
Intercept	0.054**	3.836**	−2.783**	2.023	1.273	0.300
	(2.08)	(2.12)	(−2.38)	(1.39)	(1.31)	(1.21)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.131	0.026	0.114	0.214	0.000	0.019
Observations	76,575	32,873	60,119	37,822	32,873	32,873

(Continues)

TABLE 5 (Continued)

Note: This table contains the regression results explaining the insider trading patterns and long-term trading profitability based on the centrality of insider networks and other variables. *TRADESIZE* is the number of shares traded divided by the total number of shares outstanding on the day of the trade multiplied by 100. *MULTITRADES* equals 1 if the insider executes more than one transaction of the same type (purchase or sale) on the same day. *NTRADES* is the total number of trades executed by an insider within a given year. *BAD NEWS SALE* equals 1 if the insider engages in a sale transaction before "bad news" events. We define bad news events as days in which the market-adjusted return is less than 5%. *QDEGREE* is the quartile rank formed each year based on degree centrality as defined in Subsection 3.1. In columns (3), (5), and (6), *TRADESIZE* is the average transaction size over the entire year. All other variables are as defined in Table 4. The *t*-statistics based on firm cluster robust standard errors are shown in parentheses.
Abbreviation: OLS, ordinary least squares.
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

5 | ADDITIONAL ANALYSIS

5.1 | Long-term value relevance and information asymmetry

Previous evidence suggests that insider trading generates abnormal returns when the information asymmetry between the firm and its shareholders is high (e.g., Huddart & Ke, 2007; Kraft et al., 2014). Therefore, we explore whether the long-term effect of networks is more prominent when the information environment of the firm is poor. We proxy for information environment of the firm through firm size, transaction size, and idiosyncratic volatility. Small firms are more likely to be opaque (Ball & Shivakumar, 2005; Burgstahler et al., 2006), resulting in higher information asymmetries. Transaction size, on the other hand, measures the information content of the trade (Fidrmuc et al., 2013). As a larger trade size signals greater information content, we expect larger trades of networked insiders to have more long-term price effects. Finally, idiosyncratic volatility captures the underlying firm-level risk and is used as a proxy for information asymmetry (see, e.g., Haggard et al., 2015).[29]

Table 6 reports results based on this specification. Consistent with our predictions, the long-term effect of insider trading is significantly higher for smaller firms and firms with higher idiosyncratic volatility. For example, the coefficient on *QDEGREE* is economically larger for both insider purchases and sales in the bottom two terciles of firm size. The coefficient test suggests that the difference between small and large firms and firms with high and low idiosyncratic volatility is also statistically significant. Furthermore, larger trade size is associated with more long-term effect on the stock price, indicating that trading larger volumes of stock may indicate more information about the firm's short and long-term prospects. However, the coefficient test indicates that the difference is not statistically significant.[30]

5.2 | Civic norms and societal trust

Previous evidence suggests that civic norms and societal trust influence corporate and executive behavior through the pressure of social norms (Guan et al., 2020; Kanagaretnam et al., 2018; Pevzner et al., 2015). Gębka et al. (2017) argue that as insider trading may be seen as opportunistic and costly to the shareholders, certain societies might discourage managers in engaging in such activities. In contrast, Fidrmuc et al. (2013) argue that higher levels of governance and trust enhance the transparency of insiders' activities and thereby information is incorporated in stock prices more efficiently. As a result, the long-term relevance of insider trading may be higher in societies with higher levels of trust. We test these two competing explanations in this section.

[29] We measure idiosyncratic volatility as the annual standard deviation of daily factor-adjusted returns.

[30] One potential concern in a cross-country sample is the differences in the legal regimes. Although firms in the EU are subject to the same general restrictions as per the Market Abuse Directive (2004/72/EC) throughout our sample period, in Table A.5 of the Appendix in the Supporting Information, we also test whether country's legal origin influences our results. We find that the statistical significance of abnormal returns persists regardless of legal origin of the sample countries.

TABLE 6 Long-term valuation consequences of insider trades and networks: Sensitivity analysis

Panel A: Insider purchases									
	Dependent variable: *CAR (0,180)*								
Characteristic:	**Firm size**			**Trade size**			**Idiosyncratic volatility**		
Tercile:	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Low**	**Medium**	**High**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
QDEGREE	2.511***	3.124***	1.627***	2.582***	2.551***	3.034***	0.902	2.307***	4.092***
	(4.17)	(5.72)	(3.16)	(4.29)	(6.09)	(5.62)	(1.62)	(4.69)	(6.38)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.215	0.269	0.187	0.330	0.202	0.192	0.237	0.319	0.208
Observations	18,002	15,285	13,831	16,089	15,851	15,178	15,050	14,851	17,217
H_0: Coefficient test	0.020			0.247			0.000		
Panel B: Insider sales									
	Dependent variable: *CAR (0,180)*								
Characteristic:	**Firm size**			**Trade size**			**Idiosyncratic volatility**		
Tercile:	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Low**	**Medium**	**High**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
QDEGREE	4.625***	2.590***	0.749	2.504**	3.221***	2.578***	−0.322	2.593***	5.220***
	(4.52)	(4.41)	(0.88)	(2.39)	(4.63)	(4.78)	(−0.72)	(4.29)	(4.82)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.279	0.243	0.258	0.290	0.208	0.206	0.204	0.284	0.250
Observations	7553	10,438	11,466	9451	9734	10,272	10,660	10,697	8100
H_0: Coefficient test	0.000			0.880			0.000		

Note: This table contains the sensitivity analysis for regression results explaining the long-term valuation consequences of insider trades based on the centrality of insider networks and other variables. The samples are divided into terciles based on the values of firm size, trade size, and idiosyncratic volatility. *CAR* is the cumulative abnormal return over the specified number of days following the trade date, multiplied by 100. Firm-specific *CAR* is estimated using the Fama and French (1993) and Carhart (1997) four-factor models over (−200,−21) trading days. *QDEGREE* is the quartile rank formed each year based on degree centrality as defined in Subsection 3.1. All other variables in Table 4 are included, but the results are omitted. The *t*-statistics based on firm cluster robust standard errors are shown in parentheses. The coefficient test gives the *p*-value for the test of significance of the difference between the coefficients of *QDEGREE* in the top and bottom terciles.
** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

To measure the degree of civic cooperation and societal trust, we follow Knack and Keefer (1997), among others, and use the EVS integrated data set.[31] The EVS is a survey conducted periodically in most European countries and is frequently employed in the sociology, economics, and political science literature to measure trust and social capital

[31] EVS is conducted over several waves. We combine these surveys and create a time series data set for each country spanning over the sample period. For years when the survey is not available, we backfill the data set based on the most recent survey values.

in European countries.[32] We follow this literature and calculate the degree of civic cooperation using responses to survey questions pertaining to whether the certain behaviors "can always be justified, never be justified or something in between." These behaviors include: (a) "claiming government benefits that you are not entitled to"; (b) "avoiding a fare on public transport"; (c) "cheating on taxes if you have the chance"; (d) "keeping money that you have found"; (e) "failing to report damage you have done accidentally to a parked vehicle."

The responses range from 1 = *never justifiable* to 10 = *always justifiable*. We follow Knack and Keefer (1997) and reverse these scales and sum them over the five questions, so greater values indicate higher cooperation. To measure the level of trust in a country, we use the average response of people surveyed in a given year who replied, "most people can be trusted" to the question, "Generally speaking, would you say that most people can be trusted, or that you cannot be too careful in dealing with people?".

Using these measures, we divide our sample into high (low) civic norms or societal trust based on whether the country's score falls above (below) the median value for the 16 countries in the sample. We find that the long-term relevance of insider trades by networked insiders is more pronounced in countries where civic cooperation and trust are higher. The results presented in columns (1)–(4) of Table 7 show that the coefficient for both insider purchases and sales of networked insiders is economically higher and statistically significant in countries with higher civic norms and societal trust. This further supports the notion that networked insiders do not exploit their informational advantage, but rather the market perceives their purchases as more informative and their sales as less opportunistic in the long run.

5.3 | Country-level governance

We further investigate how the level of regulatory quality influences the relation between centrality and long-term abnormal returns. To proxy for the quality of regulations in the country, we use the country-level indicators of Kaufmann et al. (2009). These indicators are composed of several hundred variables measuring political stability, government effectiveness, regulatory quality, enforcement of the rule of law, corruption, and the extent to which a country's citizens are able to participate in selecting their government. We follow Beltratti and Stulz (2012) and consider the first principal component of the six variables for each country. These variables are called voice, political stability, government effectiveness, regulatory quality, rule of law, and absence of corruption.

We divide our sample based on the median value of the governance index. Results provided in Table 7, columns (5) and (6), indicate that purchases by networked insiders are positively associated with long-term abnormal returns in both low and high governance countries. However, the difference is statistically insignificant between the two subsamples. For sales of networked insiders, the centrality–return relation is stronger in countries with higher governance scores. The magnitude is economically significant. Moreover, the coefficient test indicates that the difference between the two samples is also statistically significant. This result is largely consistent with the findings of Fidrmuc et al. (2013), who show that insider trades in high shareholder protection countries are associated with higher long-term abnormal returns.

5.4 | Equity compensation

The proportion of executive compensation paid in equity-related instruments can influence the trading patterns of insiders. Insiders in countries where a higher proportion of the compensation comes in the form of equity grants are more likely to engage in insider trading for liquidity or diversification reasons (Fidrmuc et al., 2013; Gębka et al., 2017).

[32] See, for instance, Knack and Keefer (1997), Stolle and Hooghe (2005), and Sarracino and Mikucka (2017), among others.

TABLE 7 Long-term valuation consequences of insider trades and networks: Cross-country differences

Panel A: Insider purchases								
	Dependent variable: *CAR (0,180)*							
Country characteristic:	***Civic norms***		***Societal trust***		***Country governance***		***Equity pay***	
Level:	**Low**	**High**	**Absent**	**Present**	**Low**	**High**	**Low**	**High**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
QDEGREE	2.467***	3.615***	2.577***	3.489***	2.853***	2.842***	3.227***	1.886***
	(5.58)	(5.67)	(5.23)	(6.17)	(5.54)	(5.37)	(5.72)	(3.76)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.180	0.206	0.180	0.200	0.233	0.210	0.203	0.153
Observations	24,236	17,329	22,478	19,087	25,551	21,567	22,113	13,003
H_0: Coefficient test	0.001		0.006		0.971		0.000	
Panel B: Insider sales								
	Dependent variable: *CAR (0,180)*							
Country characteristic:	***Civic norms***		***Societal trust***		***Country governance***		***Equity pay***	
Level:	**Low**	**High**	**Absent**	**Present**	**Low**	**High**	**Low**	**High**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
QDEGREE	2.632***	4.073***	2.071***	4.559***	2.030***	4.086***	3.379***	1.284**
	(4.41)	(4.11)	(3.14)	(4.35)	(3.22)	(4.28)	(5.97)	(2.02)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.217	0.265	0.207	0.275	0.204	0.260	0.225	0.198
Observations	16,396	10,776	16,783	10,389	18,219	11,238	17,434	5147
H_0: Coefficient test	0.001		0.000		0.000		0.000	

Note: This table contains the sensitivity analysis for regression results explaining the long-term valuation consequences of insider trades based on the centrality of insider networks and other variables. *CAR* is the cumulative abnormal return over the specified number of days following the trade date, multiplied by 100. Firm-specific *CAR* is estimated using the Fama and French (1993) and Carhart (1997) four-factor models over (−200,−21) trading days. *QDEGREE* is the quartile rank formed each year based on degree centrality as defined in Subsection 3.1. High (low) values are based on whether the country-level values are above (below) median values for the 16 countries in the sample. *Civic norms* is defined as the average strength of norms of civic cooperation assessed from responses to questions in the European Values Survey (EVS). *Societal trust* is defined as the average level of trust in others in a country assessed from responses to questions in the EVS (see Subsection 5.2). *Country governance* is the first principal component of six governance indicators for each country (see Subsection 5.3). *Equity pay* is the mean ratio of equity-linked pay to total CEO pay in the country, as reported in Fernandes et al. (2013). All other variables in Table 4 are included, but the results are omitted. The *t*-statistics based on firm cluster robust standard errors are shown in parentheses. The coefficient test gives the *p*-value for the test of significance of the difference between the coefficients of *QDEGREE* in the two columns for each country characteristic.

** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

We thus expect excess returns to be lower in such countries. In columns (7) and (8) of Table 6, we document evidence consistent with this expectation.

6 | CONCLUSION

In this study, we examine the long-term valuation consequences of insider trades executed by networked insiders in 16 European countries over the period 2004–2018. Using insider transaction data, we first show that there is no significant difference in the market reaction to trades of well-connected insiders and less-connected insiders. However, using longer windows of CARs, we document robust evidence of long-term value relevance of insider trades executed by well-connected insiders. We also show that networked insiders trade less frequently, exchange lower volumes of stocks, are unlikely to trade multiple times on the same day, and do not earn long-term abnormal dollar profits. This shows that insiders with more central networks are unlikely to exploit their informational advantage for economic rents.

These findings are in contrast to the recent evidence from the United Kingdom, which documents only short-term value relevance of insider trades executed by well-connected insiders. We carry out several robustness checks to reduce concerns of endogeneity and alternative explanations. We show that the effect of networks on long-term valuation is significantly higher for firms with higher information asymmetry. Finally, we build on the heterogeneity of our sample and reveal several important country-level determinants of the long-term value relevance.

Our results add new insights to how insider networks influence corporate and individual decisions. We also add to the insider trading literature by showing an important determinant of long-term value relevance—network centrality. Overall, our findings support the notion that networks facilitate the flow of information and that insiders with more channels of information are unlikely to exploit their advantage for economic rents but are more likely to convey their private information through insider trading, consequently making prices more efficient. We explore several culture and governance-related determinants of the centrality–return relation.

ACKNOWLEDGMENTS

The authors are thankful for the helpful comments provided by the two anonymous referees, participants of 26th Annual Conference of the Multinational Finance Society in Jerusalem, June 2019; 17th Finance, Risk, and Accounting Perspectives Conference in Helsinki, September 2019; and National Accounting Conference in Linköping, November 2019. They are especially grateful to Gonul Colak, Vasiliki Athanasakou, Sami Vähämaa, and C.S. Agnes Cheng for reviewing an earlier version of this manuscript.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

REFERENCES

Aboody, D., Hughes, J., & Liu, J. (2005). Earnings quality, insider trading, and cost of capital. *Journal of Accounting Research*, *43*(5), 651–673.

Afzali, M., & Kettunen, J. (2020). *Board centrality and firm performance: Evidence from private firms*. SSRN Working Paper.

Aguilera, M. B. (2002). The impact of social capital on labor force participation: Evidence from the 2000 Social Capital Benchmark Survey. *Social Science Quarterly*, *83*(3), 853–874.

Ahern, K. R., Daminelli, D., & Fracassi, C. (2015). Lost in translation? The effect of cultural values on mergers around the world. *Journal of Financial Economics*, *117*(1), 165–189.

Akbas, F., Meschke, F., & Wintoki, M. B. (2016). Director networks and informed traders. *Journal of Accounting and Economics*, *62*(1), 1–23.

Aktas, N., de Bodt, E., & Van Oppens, H. (2008). Legal insider trading and market efficiency. *Journal of Banking and Finance*, *32*(7), 1379–1392.

Ausubel, L. M. (1990). Insider trading in a rational expectations economy. *American Economic Review*, *80*(5), 1022–1041.

Bajo, E., Chemmanur, T. J., Simonyan, K., & Tehranian, H. (2016). Underwriter networks, investor attention, and initial public offerings. *Journal of Financial Economics*, *122*(2), 376–408.
Ball, R., & Shivakumar, L. (2005). Earnings quality in UK private firms: Comparative loss recognition timeliness. *Journal of Accounting and Economics*, *39*(1), 83–128.
Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: An open source software for exploring and manipulating networks. *International AAAI Conference on Weblogs and Social Media*, *25*, 361–362.
Beltratti, A., & Stulz, R. M. (2012). The credit crisis around the globe: Why did some banks perform better? *Journal of Financial Economics*, *105*(1), 1–17.
Benson, B. W., Iyer, S. R., Kemper, K. J., & Zhao, J. (2018). Director networks and credit ratings. *Financial Review*, *53*(2), 301–336.
Brooks, C., Godfrey, C., Hillenbrand, C., & Money, K. (2016). Do investors care about corporate taxes? *Journal of Corporate Finance*, *38*, 218–248.
Brown, J. L. (2011). The spread of aggressive corporate tax reporting: A detailed examination of the corporate-owned life insurance shelter. *The Accounting Review*, *86*(1), 23–57.
Brown, J. L., & Drake, K. D. (2014). Network ties among low-tax firms. *The Accounting Review*, *89*(2), 483–510.
Burgstahler, D. C., Hail, L., & Leuz, C. (2006). The importance of reporting incentives: Earnings management in European private and public firms. *The Accounting Review*, *81*(5), 983–1016.
Burt, R. S. (1995). *Structural holes: The social structure of competition*. Harvard University Press.
Burt, R. S. (2005). *Brokerage and closure: An introduction to social capital*. Oxford University Press.
Cai, J., Walkling, R. A., & Yang, K. (2016). The price of street friends: Social networks, informed trading, and shareholder costs. *Journal of Financial and Quantitative Analysis*, *51*(3), 801–837.
Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, *52*(1), 57–82.
Cheng, Q., & Kin, L. O. (2006). Insider trading and voluntary disclosures. *Journal of Accounting Research*, *44*(5), 815–848.
Cohen, L., Frazzini, A., & Malloy, C. (2008). The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy*, *116*(5), 951–979.
Cohen, L., Malloy, C., & Pomorski, L. (2012). Decoding inside information. *Journal of Finance*, *67*(3), 1009–1043.
Coleman, J. S. (1994). *Foundations of social theory*. Harvard University Press.
Cziraki, P., Lyandres, E., & Michaely, R. (2019). What do insiders know? *Evidence from insider trading around share repurchases and SEOs. Journal of Corporate Finance*, *66*, 101544.
El-Khatib, R., Fogel, K., & Jandik, T. (2015). CEO network centrality and merger performance. *Journal of Financial Economics*, *116*(2), 349–382.
Engelberg, J., Gao, P., & Parsons, C. A. (2012). Friends with money. *Journal of Financial Economics*, *103*(1), 169–188.
Engelberg, J., Gao, P., & Parsons, C. A. (2013). The price of a CEO's rolodex. *Review of Financial Studies*, *26*(1), 79–114.
Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56.
Fernandes, N., Ferreira, M. A., Matos, P., & Murphy, K. J. (2013). Are U.S. CEOs paid more? New international evidence. *Review of Financial Studies*, *26*(2), 323–367.
Ferris, S. P., Javakhadze, D., & Rajkovic, T. (2017a). CEO social capital, risk-taking and corporate policies. *Journal of Corporate Finance*, *47*, 46–71.
Ferris, S. P., Javakhadze, D., & Rajkovic, T. (2017b). The international effect of managerial social capital on the cost of equity. *Journal of Banking and Finance*, *74*, 69–84.
Fidrmuc, J. P., Goergen, M., & Renneboog, L. (2006). Insider trading, news releases, and ownership concentration. *Journal of Finance*, *61*(6), 2931–2973.
Fidrmuc, J. P., Korczak, A., & Korczak, P. (2013). Why does shareholder protection matter for abnormal returns after reported insider purchases and sales? *Journal of Banking and Finance*, *37*(6), 1915–1935.
Fishman, M. J., & Hagerty, K. M. (1992). Insider trading and the efficiency of stock prices. *The RAND Journal of Economics*, *23*(1), 106–123.
Fogel, K., Jandik, T., & McCumber, W. R. (2018). CFO social capital and private debt. *Journal of Corporate Finance*, *52*, 28–52.
Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, *111*(1), 1–25.
Friederich, S., Gregory, A., Matatko, J., & Tonks, I. (2002). Short-run returns around the trades of corporate insiders on the London stock exchange. *European Financial Management*, *8*(1), 7–30.
Gębka, B., Korczak, A., Korczak, P., & Traczykowski, J. (2017). Profitability of insider trading in Europe: A performance evaluation approach. *Journal of Empirical Finance*, *44*, 66–90.
Goergen, M., Renneboog, L., & Zhao, Y. (2019). Insider trading and networked directors. *Journal of Corporate Finance*, *56*, 152–175.
Guan, Y., Lobo, G. J., Tsang, A., & Xin, X. (2020). Societal trust and management earnings forecasts. *The Accounting Review*, *95*(5), 149–184.

Haggard, K. S., Howe, J. S., & Lynch, A. A. (2015). Do baths muddy the waters or clear the air? *Journal of Accounting and Economics*, *59*(1), 105–117.
He, X., Pittman, J. A., Rui, O. M., & Wu, D. (2017). Do social ties between external auditors and audit committee members affect audit quality? *The Accounting Review*, *92*(5), 61–87.
Hillier, D., Korczak, A., & Korczak, P. (2015). The impact of personal attributes on corporate insider trading. *Journal of Corporate Finance*, *30*, 150–167.
Hillier, D., & Marshall, A. P. (2002). Are trading bans effective? Exchange regulation and corporate insider transactions around earnings announcements. *Journal of Corporate Finance*, *8*(4), 393–410.
Horton, J., Millo, Y., & Serafeim, G. (2012). Resources or power? Implications of social networks on compensation and firm performance. *Journal of Business Finance and Accounting*, *39*(3–4), 399–426.
Huddart, S. J., & Ke, B. (2007). Information asymmetry and cross-sectional variation in insider trading. *Contemporary Accounting Research*, *24*(1), 195–234.
Javakhadze, D., Ferris, S. P., & French, D. W. (2016a). Social capital, investments, and external financing. *Journal of Corporate Finance*, *37*, 38–55.
Javakhadze, D., Ferris, S. P., & French, D. W. (2016b). Managerial social capital and financial development: A cross-country analysis. *Financial Review*, *51*(1), 37–68.
Javakhadze, D., & Rajkovic, T. (2018). How friends with money affect corporate cash policies? The international evidence. *European Financial Management*, 25, 11–21.
Jeng, L. A., Metrick, A., & Zeckhauser, R. (2003). Estimating the returns to insider trading: A performance-evaluation perspective. *Review of Economics and Statistics*, *85*(2), 453–471.
Jenter, D. (2005). Market timing and managerial portfolio decisions. *The Journal of Finance*, *60*(4), 1903–1950.
Kanagaretnam, K., Lee, J., Lim, C. Y., & Lobo, G. (2018). Societal trust and corporate tax avoidance. *Review of Accounting Studies*, *23*(4), 1588–1628.
Kandori, M. (1992). Social norms and community enforcement. *The Review of Economic Studies*, *59*(1), 63–80.
Karolyi, G. A. (2016). The gravity of culture for finance. *Journal of Corporate Finance*, *41*, 610–625.
Kaufmann, D., Kraay, A., & Mastruzzi, M. (2009). *Governance matters VIII: Aggregate and individual governance indicators 1996–2008*. The World Bank.
Ke, B., Huddart, S., & Petroni, K. (2003). What insiders know about future earnings and how they use it: Evidence from insider trades. *Journal of Accounting and Economics*, *35*(3), 315–346.
Knack, S., & Keefer, P. (1997). Does social capital have an economic payoff? A cross-country investigation. *Quarterly Journal of Economics*, *112*(4), 1251–1288.
Kraft, A., Lee, B. S., & Lopatta, K. (2014). Management earnings forecasts, insider trading, and information asymmetry. *Journal of Corporate Finance*, *26*, 96–123.
Lakonishok, J., & Lee, I. (2001). Are insider trades informative? *Review of Financial Studies*, *14*(1), 79–111.
Larcker, D. F., So, E. C., & Wang, C. C. Y. (2013). Boardroom centrality and firm performance. *Journal of Accounting and Economics*, *55*(2–3), 225–250.
Leland, H. E. (1992). Insider trading: Should it be prohibited? *Journal of Political Economy*, *100*(4), 859–887.
Lin, N. (1999a). Building a network theory of social capital. *Connections*, *22*(1), 28–51.
Lin, N. (1999b). Social networks and status attainment. *Annual Review of Sociology*, *25*(1), 467–487.
Lin, N. (2001). *Social capital: A theory of social structure and action*. Cambridge University Press.
McMillan, J., & Woodruff, C. (2000). Private order under dysfunctional public order. *Michigan Law Review*, *98*(8), 2421–2458.
Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics*, *58*(1–2), 215–260.
Narayanan, R. (2000). Insider trading and the voluntary disclosure of information by firms. *Journal of Banking and Finance*, *24*(3), 395–425.
Nooy, W. D.e, Mrvar, A., & Batagelj, V. (2018). *Exploratory social network analysis with Pajek*. Cambridge University Press.
Pevzner, M., Xie, F., & Xin, X. (2015). When firms talk, do investors listen? The role of trust in stock market reactions to corporate earnings announcements. *Journal of Financial Economics*, *117*(1), 190–223.
Piotroski, J. D., & Roulstone, D. T. (2004). The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. *The Accounting Review*, *79*(4), 1119–1151.
Piotroski, J. D., & Roulstone, D. T. (2005). Do insider trades reflect both contrarian beliefs and superior knowledge about future cash flow realizations? *Journal of Accounting and Economics*, *39*(1), 55–81.
Rauch, J. E., & Casella, A. (2003). Overcoming informational barriers to international resource allocation: Prices and ties. *Economic Journal*, *113*(484), 21–42.
Ravina, E., & Sapienza, P. (2010). What do independent directors know evidence from their trading. *Review of Financial Studies*, *23*(3), 962–1003.
Rossi, A., & Sahlström, P. (2019). Equity issuance motives and insider trading. *Journal of Corporate Finance*, *58*, 726–743.

Sarracino, F., & Mikucka, M. (2017). Social capital in Europe from 1990 to 2012: Trends and convergence. *Social Indicators Research*, *131*(1), 407–432.

Seyhun, H. N. (1986). Insiders' profits, costs of trading, and market efficiency. *Journal of Financial Economics*, *16*(2), 189–212.

Spagnolo, G. (1999). Social relations and cooperation in organizations. *Journal of Economic Behavior and Organization*, *38*(1), 1–25.

Stolle, D., & Hooghe, M. (2005). Inaccurate, exceptional, one-sided or irrelevant? The debate about the alleged decline of social capital and civic engagement in western societies. *British Journal of Political Science*, *35*(1), 149–167.

Wang, W., Shin, Y.-C., & Francis, B. B. (2012). Are CFOs' trades more informative than CEOs' trades? *Journal of Financial and Quantitative Analysis*, *47*(4), 743–762.

Wu, W. P. (2008). Dimensions of social capital and firm competitiveness improvement: The mediating role of information sharing. *Journal of Management Studies*, *45*(1), 122–146.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Afzali M, Martikainen M. Network centrality and value relevance of insider trading: Evidence from Europe. *Financial Review*. 2021;*56*:793–819. https://doi.org/10.1111/fire.12277